Does Background Risk Matter?
Evidence from Insurers' Corporate Bond Portfolios

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Abstract

Theory suggests that investors facing more non-hedgeable background risk may behave as if they were more risk averse in investment decisions. In this study, we examine how operating risk of US insurance firms affects their risk taking behavior in the corporate bond market. Insurers with higher volatilities in underwriting income and cash flows have lower credit risk exposure in their corporate bond portfolios. Further, insurers' credit risk exposure is more sensitive to the risk of permanent underwriting income/cashflow shocks than to the risk of transitory shocks. There is evidence that transitory operating risk is a significant determinant of credit risk taking when insurers face tight financing constraints. We also find that higher operating risk insurers experience less investment losses in the recent financial crisis than low operation risk insurers. Considering operating risk as a main source of background risk of insurers' investment risk taking, the negative association between insurer operating risk and investment risk is consistent with the theoretical background risk effect on portfolio decisions. Our findings suggest that background risk potentially provides an explanation for the inter-connection between seemingly unrelated risks across various sectors of the financial market.

Key words: Background risk; Credit Risk; Operating Risk; Financial Constraints

1. Introduction

Financial institutions often hold large investment portfolios in addition to running their main business in various segments of the financial market. For example, investment banks' main business is to advise corporate clients on securities issuance, restructuring, and M&A activities, but they often have proprietary trading desks that bet large amounts of firm capital. Investment activities generate a large proportion of profit as well as a large amount of risk to financial institutions.[1] As another example, insurers' main line of business is to underwrite life or property policies, collect premiums, and manage claim payouts. In the meantime, they are among most important investors in the fixed income market. Their investments in the corporate bond market are particularly sizeable.

How financial institutions manage investment risk vis-$\grave{a}$-vis the risk they face in their main business operations is a prominent issue. Are these two types of risks managed independently, or managed as compliments or substitutes? At the firm level, these questions are an important element of financial institutions' risk management practice that interests both practitioners and academia. At the market level, researchers have been trying to understand why seemingly unrelated segments of the financial market may suddenly act together, giving rise to financial contagion. Part of the answer may lie in the way institutions manage risks across market segments—although the risks of various market segments (i.e., the securities market an institution invests and the market segment it mainly operates in) may be uncorrelated, the risk-taking decisions of institutions across these segments could well be dependent. Finally, the issue is also relevant from a policy-making or regulatory perspective. Consider the debate on regulating excessive risk taking in financial institutions' proprietary trading activities.[2] In order for the regulators to decide a proper limit on investment risk an institution should take, it is necessary to know whether there is an acceptable or prudent level of investment risk in relation to the operation risk it faces.

In this study, using data on U.S. insurance firms, we empirically examine a prediction that

[1] For example, in the recent financial crisis during 2007-2009, the profit reaped by the trading desks of Goldman Sachs, and the loss incurred at the trading desks of Morgan Stanley, respectively dominated the operating results of all other units of the two investment banks.

[2] The Volcker rule as part of the Dodd-Franck Act of 2010, for example, virtually restricts financial institutions from any type of proprietary trading, out of the concern that such trading increases the systemic risk.

the risks financial institutions face in their main business operations (hereafter "operating risk")[3] have a substitutive effect on their risk-taking behavior in portfolio investments. That is, when an institution faces higher operating risk, it may choose to reduce the level of investment risk it takes. As elaborated below, this prediction finds support from two strands of finance theory, one on background risk and another on corporate risk management and hedging.

The theory of background risk is developed in the early academic literature that strives to understand economic agents' attitude toward multiple sources of risks. The gist of this theory is that investors facing more non-hedgeable background risk may behave as if they were more risk averse when making investment decisions (e.g., Pratt and Zeckhauser 1987; Kimball, 1993; Gollier and Pratt 1996; Eekhoudt, Gollier, and Schlesinger 1996; Fei and Schlesinger 2008). For individuals, such non-hedgeable risks are from their labor incomes, entrepreneurial incomes, and housing, etc., and there is a growing body of empirical studies that documents how these various forms of background risk affect individual investors' investments (e.g., Guiso, Jappellio and Terilizzesse 1996; Gakidis 1997; Heaton and Lucas; 2000b; Gentry and Hubbard, 2000; Yao and Zhang, 2005; Palia, Qi and Wu, 2007). For financial institutions, operating risk can be viewed as a type of background risk when examining their risk-taking in portfolio investments. However, the background risk theory is developed originally to describe the risk-taking behavior of individual agents with well-defined risk preferences; whether it can guide us to understand the risk-taking behavior of financial institutions has yet to be addressed by empirical studies.

A second strand of the theory, developed by a series of studies such as Froot, Scharfstein, and Stein (1993), Froot and Stein (1998), and Froot (2007), provides a concrete assumption on corporate risk aversion and describes corporate incentives to risk management hedging. This corporate risk management literature suggests that firms may behave in a risk averse way due to convex external financing cost. The part of the theory that has attracted most of the attention in empirical studies is its implication on hedging–that is, a firm should not take (or should hedge away) any tradable risk unless the firm has expertise in that risk source that allows it to generate returns above the fair compensation for risk in the financial market. Less scrutinized by empirical studies but directly relevant to our study, is that the theory's implication for a substitutive effect across

[3]The term operating risk here is different from the notion of "operational risk" (as defined in Basel II, for example), which refers to the risk from inadequate or failed internal processes, people and systems.

multiple sources of risks a firm takes. Specifically, the theory suggests that given convex external financing costs, the hurdle rate for evaluating an investment not only increases in the investment's exposure to priced market-wide risk factors, but also in the total risk the firm already faces and the contribution to the total risk by the new investment. Thus, risk-taking in one investment increases the hurdle rate and thus effectively reduces the risk-taking in another investment, even when the returns of the two investments are uncorrelated.

Despite originating from different perspectives, both theories suggest that financial institutions facing higher risk in their main business would invest more conservatively. To our knowledge, this implication has not been examined empirically in the existing literature. Possibly, a main hurdle to carry out such research is the data availability — due to various reasons such as competition concerns, financial institutions are typically reluctant to disclose the revenue they generate and the risk they face in their investment activities. For example, investment banks guard information on the risk and profitability of their proprietary trading business as top secret.

We employ a newly available data on the investment portfolios of insurance firms, and analyze how insurers manage their risk-taking in the corporate bond market in relation to the risk in their insurance operations. We focus on the effect of insurers' operating risk on their investment decisions, not the other way around, because insurers face much higher adjustment costs to alter their insurance products in comparison to the costs to adjust their investment portfolios. In other words, insurance operating risk is determined by factors influencing the demand and supply in the insurance product market, largely exogenous to the changes in credit risks in the corporate bond market. On the other hand, the uncertainty in the insurance product market could quickly influence the amount of risk an insurer is willing to take in the corporate bond market.

The investment portfolios of insurance firms consist of a rich spectrum of securities, ranging from Treasuries, agency bonds, corporate bonds, mortgage- and asset-backed securities, to common and preferred stocks and derivative instruments. Out of the entire spectrum of financial risks they take, we single out corporate credit risk for analysis (while controlling for other sources of financial risk) for the following reasons. First, credit risk is a very important dimension of insurers' investment decisions given their substantial stake in corporate bonds. Corporate bonds are the single largest type of financial assets in insurers' investment portfolios. According to the Federal

Reserve Flow of Funds Accounts report, at the end of 2008 insurance companies invest over 35% of their assets in corporate bonds, and they collectively hold over 30% of the outstanding U.S. corporate bonds. Second, corporate credit risk is largely unrelated to the underwriting risk insurers face in their main business. Therefore, the empirical relation between credit risk and insurance operating risk represents a relative clean case for the substitutive effect predicted by the theories. By contrast, interest rate risk of insurers' investment portfolios is typically related to the interest rate risk of their operating liabilities (e.g., Chen, Sun, Yao, and Yu, 2013), and insurers hold stocks mainly to hedge the equity exposure in their equity-linked variable annuity products. In other words, insurers' portfolio exposure to interest rate risk and stock market risk could well be explained by the hedging motives rather than by the substitution effect of risk-taking.

In testing the effect of operating risk on insurers' credit risk taking, we combine various sources of information to construct a comprehensive database on insurers' operating characteristics, their corporate bond holdings and trades, as well as characteristics of each bond, for a 15-year sample period from 1996 and 2010. To quantify the operating risk, we consider two comprehensive measures for insurers' aggregated risk taking in their insurance underwriting business: the volatility of underwriting income and the volatility of non-investment underwriting cash flows. We measure the portfolio credit risk exposure by the weighted average credit ratings and yield spreads on individual bonds held in a portfolio.

We empirically examine two versions of the risk substitution effect. The first is a static effect. The early theoretical development on background risk is typically in a static setting, where the aggregate background risk matters. Subsequent studies analyze the problem in a multi-period setting and introduce the possibility of inter-temporal smoothing (via saving and borrowing), which gives rise to the second version, i.e., the dynamic effect of background risk. For example, Heaton and Lucas (1997) show that inter-temporal smoothing enables investors to borrow and lend money to smooth out temporary, non-persistent shocks to labor income without significantly affecting their stock investment or consumption decisions. In other words, the ability of inter-temporal smoothing is an important factor for determining the effect of background risk. Such an ability is, in turn, affected by factors such as the persistence of background-risk shocks as well as borrowing constraints, short-sale constraints, and transaction costs (see, e.g., Aiyagari and Gertler 1991; Aiyagari

1994; Heaton and Lucas 1997). We term the effect of inter-temporal smoothing on the relation between background risk and investment decisions the "dynamic" effect. Whether the dynamic effect exists is an interesting question to explore empirically, as there is already strong evidence that financial constraints are important in understanding insurers' financing and operating decisions. For example, many studies in the insurance literature document the cyclical pattern of underwriting profitability, and attribute such cyclicality to capacity constraints and financial constraints caused by capital market imperfection (Winter 1994; Gron 1994; Harrington and Niehaus 2000).

The corporate risk management models developed by Froot, Scharfstein, and Stein (1993), Froot and Stein (1998), and Froot (2007) are also static in nature. Therefore, the direct implication from these models is a substitutive effect between the total operating risk and credit risk in corporate bond portfolios. However, it is conceivable – although beyond the scope of this empirical paper – to extend their models to a dynamic setting that delivers something similar to the dynamic background risk effect.

Our empirical analysis uncovers strong evidence for the static substitution effect of operating risk on insurers' corporate bond investments. The weighted-average credit ratings of insurers' corporate bond holdings are positively related to volatilities in the underwriting incomes and the volatilities in non-investment cash flows, and the weighted-average credit spreads of corporate bond holdings are inversely related to the amount of operating risks insurers take. In other words, insurers with greater operating risks prefer bonds with higher credit ratings and lower credit spreads (both indicative of lower credit risk). The result remains robust after we control for various firm characteristics, and insurers' risk-taking in other types of securities, such as government bonds and equities.

We further perform two sets of analysis on the dynamic substitution effect of operating risk. First, we decompose the shocks to underwriting incomes and underwriting cash flows into persistent and temporary components. The predicted dynamic effect is that when insurers have some ability to smooth short-term cash flow shocks, only the risk of persistent operating shocks matters for corporate credit risk taking. Consistent with this prediction, our analysis shows that persistent operating shocks have a significant impact on the level of credit risk insurers take. By contrast, the impact of temporary operating shocks is much weaker. Secondly, we look at the effect of financing constraints in shaping the relation between operating risk and investment risk. Insurers facing tighter financing constraints have less ability to smooth shocks to their underwriting business. As a result, their investment risk-taking is more sensitive to their operating risk. Three types of insurers by nature are more likely to have financing constraints: small firms, mutual insurers, and firms not affiliated with any large parental group.[4] Consistent with our expectation, we find that the effect of background risk on credit risk taking is stronger for these subsets of insurers.

Our results are robust to alternative measures of operating risk based on insurers' firm attributes associated with their operational risk, including the leverage ratio of firm, the percentage of business in sectors having long-horizon claim payment schedules (e.g., auto and general liability insurance, workers' compensation, and medical malpractice liability insurance), the level of diversification across business sectors and geographic locations. Consistent with the theoretical prediction, we find that firms with high leverage and those operating in the long tail business and less diversified in their underwriting business take less credit risk in their corporate bond portfolios.

Last, we examine the background risk effect during the recent financial crisis, when many financial institutions suffer large losses in the credit market. If insurers subject to higher operating risk invest more conservatively, these insurers may suffer less during the crisis. The empirical finding confirms this conjecture. Over the period from 2007 to 2009, while insurers as a whole suffer investment losses, those with higher underwriting income volatility turn out to have substantially better investment performance (i.e., lower losses) than those lower underwriting income volatility.

Collectively, the evidence is consistent with a substitutive effect of operating risk on the investment decisions by financial institutions. While we do not expect this substitutive effect to fully explain insurers' credit risk taking, our findings are consistent with the common predictions from both the background risk theory and the theory on corporate risk management, and consistent with both the static and dynamic versions of the effect. To our knowledge, our study is the first to document such a substitution effect by financial institutions when they manage multiple sources of risks. This effect may help understand why and how interconnections between various segments of the financial market arise. Based on financial institutions' stock returns, Billio, Getmansky,

[4]This is because small firms have an obvious disadvantage in financing their liabilities, mutual companies are less efficient in accessing the capital market than stock companies (Lamm-Tennant and Starks 1993; Harrington and Niehaus 2000), and finally, insurers unaffiliated with any parental groups cannot receive subsidies from other insurers.

Lo, Pelizzon (2012) show a rising level of inter-connectivity among various financial sectors, including banks, insurance companies, hedge funds, and broker/dealers, over the past decade. Our findings suggest that risk substitution may play a role in giving rise to systemic risk—even though the risks from various market segments are unrelated during “normal times”, if the dependency in risk-taking decisions of financial institutions in these segments turns out to be strong, financial contagion could arise.

The remainder of the paper is organized as follows: Section 2 discusses the literature related to background risk and corporate risk management, and proposes testable implications. Section 3 discusses the data and our measures of operating risk and credit risk of corporate bond portfolios. Section 4 provides empirical evidence on the relation between bond portfolio risk and operating risk. Section 5 concludes.

2. Related Literature

2.1. Static and Dynamic Operating Risk Effects

The Economic decisions are often made in the presence of multiple risks and in markets that are less than complete. The operating risk of insurance firms may be considered as the background risks that agents, e.g., investors, simultaneously face but are not under their control when they make decisions of their investment portfolios. Under the background risk effect hypothesis, independent risks are substitutes for each other – adding a zero mean background risk to wealth should increase risk aversion to other independent risks. Risk aversion however does not sufficiently guarantee the background risk effect. Pratt and Zeckhauser (1987), Kimball (1993), and Gollier and Pratt (1996) are the most important works introducing the appropriate conditions for the presence of the background risk effect, such as proper risk aversion, standard risk aversion, and risk vulnerability, for greater risk aversion in presence of independent background risks. These studies analyze the background risk effect in a static single-period setting.

Alternatively, researchers analyze the background risk effect in a dynamic multi-period setting. Heaton and Lucas (1996) show that intertemporal smoothing enables investors to borrow and lend money to smooth out temporary, non-persistent shocks to labor income without significantly affecting their stock investment or consumption decisions. In other words, intertemporal smoothing ability is an important factor for determining the effect of background risk. Such ability is, in turn, affected by factors such as the persistence of background-risk shocks, as well as borrowing constraints, short-sale constraints, and transaction costs (see, e.g., Aiyagari and Gertler 1991; Aiyagari 1994; Heaton and Lucas 1996, 1997). Existing studies on the insurance market have suggested that financial constraints are important in understanding insurers' behavior. For example, many studies document the cyclical pattern of underwriting profitability, and attribute such cyclicality to capacity constraints caused by capital market imperfection (Winter 1994; Gron 1994; Harrington and Niehaus 2000). Time-varying underwriting profitability in the insurance industry makes investment decisions of insurance companies a relevant setting for testing the dynamic effect of background risk.

The empirical analysis on the background risk theory focuses on two specific sources of background risk exposures. The first is the labor income risk. Bodie, Merton and Samuelson (1992) show that the presence of non-tradable stochastic future labor income reduces investors' demand for risky financial assets. Koo (1998) suggests that investors will take a smaller fraction of risky assets in their portfolio when they have liquidity constraints and uninsurable income risk. Heaton and Lucas (2000a) calibrate labor income risk with personal income data. They show that both labor income risk and the positive correlation between labor income and risky asset return tend to reduce investments in risky assets. Similarly, Heaton and Lucas (2000b) examine the U.S. data and find that proprietary income risk reduces the share of risky assets in an investor's portfolio. The second source of background risk is the presence of housing ownership. Cocco (2004) analyzes the impact of a housing decision on investors' portfolio choice. He points out a "crowding out" effect where housing investments constrain investors' investments in stocks. He also demonstrates that the housing liquidation cost reduces the investor's incentive to invest in stocks. Yao and Zhang (2005) obtain similar results by modeling the portfolio choice of investors with both rental and house ownership options.

The background risk theory is developed to understand the decisions of individual agents whose risk aversions are well-defined. There is an open question on whether the same theory applies to firms or financial institutions. The main conceptual issue is whether firms behave in a risk averse way. Under the traditional view, in a frictionless financial market, firms should make investment decisions based on the net present value of the investments independently; hence risk aversion does not matter for investment decisions as long as firms choose appropriate discount rates to evaluate investments. However a recent stream of literature suggests that in the presence of market frictions, firms and financial institutions do behave in a risk-averse way when making investment and risk management decisions. Several reasons for corporate risk aversion have been identified, such as the risk aversion of corporate managers or key stakeholders (Stulz 1984), the effect of corporate tax (Smith and Stulz 1985), the cost of financial distress (Smith and Stulz 1985), and convex external financing cost (Froot, Scharfstein, and Stein, 1993; Froot and Stein, 1998; Froot, 2007). Finally, the capital adequacy regulations on financial institutions serve as an exogenous enforcement on their risk averse behavior when making investment and risk management decisions. In our view, whether the background risk effect emerges from these forms of corporate risk aversion is a question open to empirical investigation.

2.2. Corporate Risk Management and Hedging

A second strand of the theory, developed by a series of studies such as Froot, Scharfstein, and Stein (1993), Froot and Stein (1998), and Froot (2007), provides a concrete assumption on corporate risk aversion and describes corporate incentives to risk management hedging. This corporate risk management literature suggests that firms may behave in a risk averse way due to convex external financing cost. The part of the theory that has attracted most of the attention in empirical studies is its implication on hedging–that is, a firm should not take (or should hedge away) any tradable risk unless the firm has expertise in that risk source that allows it to generate returns above the fair compensation for risk in the financial market.

Less scrutinized by empirical studies but directly relevant to our study, is that the theory's implication for a substitutive effect across multiple sources of risks a firm takes. Specifically, the theory suggests that given convex external financing costs, the hurdle rate for evaluating an investment not only increases in the investment's exposure to priced market-wide risk factors, but also in the total risk the firm already faces and the contribution to the total risk by the new investment. Thus, risk-taking in one investment increases the hurdle rate and thus effectively reduces the risk-taking in another investment, even when the returns of the two investments are uncorrelated.

2.3. Testable Hypotheses

We empirically examine the operating risk effect on the portfolio decisions of institutional investors in both static and dynamic settings. Three empirical hypotheses are investigated:

- Credit risk of insurers' portfolios would be negatively associated with the aggregate operating risk faced by insurers. This is the static operating risk effect hypothesis.

- Credit risk of insurers' portfolios would be negatively associated with the permanent operating risk faced by insurers while un-correlated with transitory background risk. This is the dynamic operating risk effect hypothesis.

- Credit risk of insurers' portfolios would be negatively associated with transitory operating risk for insurers facing financial constraint. This is the financial constraint effect hypothesis.

The first two hypotheses naturally follow the literature on the background risk theory and the literature on risk management. The third hypothesis has more to do with the financial constraints faced by the insurance industry. Catastrophic events repeatedly drain capital of insurance companies, reducing insurers' ability to supply insurance (e.g., Winter, 1994; Gron, 1994). The existence of market frictions constrains insurers' ability to quickly raise capital and restore insurance supply to the pre-shock level. Given that financial constraints differ across firms, insurers with greater financial constraints have poorer ability to smooth the transitory operating risk. We therefore expect that their credit risk taking would be more sensitive to the transitory operating risk.

3. Data and Methodology

3.1. Data and Sample

The sample of property liability insurers is constructed using the information from the National Association of Insurance Commissioners database (hereafter, the NAIC database) for the period

1995 through 2009 (corresponding to insurers' corporate bond portfolios from 1996 to 2010). The database provides detailed financial statements information for more than 3,000 property liability insurers with main operations in the U.S. An interesting feature regarding the insurance industry is that a significant portion of insurance companies are affiliated with insurance holding companies (i.e., insurance groups). Both the holding companies and individual subsidiaries file financial statements to state regulators and NAIC compiles the filing and puts together the NAIC database. In our study, only individual insurers are included in the analysis to avoid double counts (by requiring the NAIC firm code, firm identifier in the NAIC database, of an insurer to be no less than 10000). We exclude data for holding companies because not all insurance groups disclose their combined financial statements to NAIC. Following prior studies such as Cummins, Dionne, Gagne, and Nouira (2007), we eliminate firms with negative surplus, assets, losses or expenses. We also require that i) sample insurers are not reinsurance companies by requiring direct premium written to be positive, and ii) sample insurers have total assets no less than USD1 million. The resulting insurer sample contains 21,513 firm-year observations and 2,290 unique property and liability firms for the 13-year period.

Our corporate bonds sample comes from schedule D of the NAIC data and the Mergent Fixed Investment Securities Database (hereafter, the Mergent FISD database) from 1996 to 2008. Schedule D of insurance companies' annual reports classifies bonds into eight categories based on the nature of the issuer. the details of Schedule D classifications are provided in Appendix A. Securities in each of the category are further broken down into 4 types based on whether a specific bond is backed by certain assets (e.g., loan-backed, collateralized mortgage obligations) or the debt is a structured product. The database provides detailed information on every bond holding for each insurer at the end of each year, including par value and fair market value of bonds and transaction information.

The Mergent FISD database provides data for all of the U.S. corporate bonds maturing from 1990. It provides comprehensive information on each bond issuance, such as the coupon rate, coupon payment frequency, maturity date, and the offering amount. We merge corporate bonds included in the schedule D database with those in the Mergent FISD database based on their

CUSIPs.[5] We select sample bonds following Campbell and Taksler (2003). In the eight types of bonds, we consider public utilities, industrial and miscellaneous bonds that are not backed by other loans as our sample corporate bonds. We also restrict our sample to fixed-rate U.S. dollar bonds that are noncallable, nonputtable, nonsinking funds, and nonconvertible.

Panel A of Table 1 shows the number of unique corporate bonds during the sample selection process. For the period of 1996 through 2008, combining corporate bonds reported in Schedule D of the NAIC database and the Mergent FISD database, we obtain 46,247 unique bonds. The enforcement of fixed-rate and other restrictions further reduce the number of bonds. We obtain a final sample with 30,436 unique corporate bonds.

Panel B of Table 1 provides summary statistics of insurers' corporate bond holdings for each sample year. The number of bonds ranges from 5,398 (year 1996) to 7,202 (year 1999). An average insurer holds 21 corporate bonds in 1996 and 34 bonds in 2008. The invested assets in corporate bonds range from \$66.42 billion in 1996 to \$108.23 billion in 2004. Insurance firms invested mostly in investment grade bonds (about 95% of corporate bond investment) rather than junk bonds. We also find that insurance firms tend to hold short term and median term bonds. For example, on average, insurers hold 48% in bonds due in five years, 41% of bonds due in 5 to 10 years, and only 11% on bonds longer than 10 years. Such tendency to hold bonds less than 10 years has been more obvious in recent years.

3.2. Operating Risk Measures

Operating risk of investment portfolios of insurance companies stems from the uncertainty of their underwriting business, jointly determined by firm operating and financial leverages. We assess the operating risk of an insurer based on the uncertainty of the insurer's profitability or cash flow from its underwriting business. To be specific, the first measure of operating risk is the standard

[5]Schedule D data provided by National Association of Insurance Commissioners (NAIC) differs from a conventionally used bond transaction database, known as the NAIC Schedule D data reconciled by Mergent. The Mergent version data consists of all 1995 to 2003 bond transactions by property and liability insurance companies, life insurance companies, and health maintenance organizations (HMOs). See Hong and Warga (2000) and Campbell and Taksler (2003) for the details of this database. There are two limitations associated with the Mergent Schedule D data. First, it does not include the identity of the insurance companies which trade the bonds. Second, it has all the trading data, but does not have the year-end holding information.

deviation of each insurer's underwriting income per dollar of the insurer's total assets:

$$UIVOL_{i,t} = Std(\frac{UI_{i,t}}{TA_{i,t}}) = Std(UI^a_{i,t}) \tag{1}$$

where underwriting income (*UI*) is from the income statement;[6] total assets (*TA*) are from the balance sheet. $UI^a_{i,t}$ is underwriting income scaled by total assets. *UIVOL* is estimated on a rolling basis: in each year t from 1996-2008, we use the prior 10 year data of an insurer to estimate its standard deviation of asset scaled underwriting income; firms with fewer than 5-year observations over the past 10-year period are excluded.

The second operating risk measure is the volatility of underwriting cash flow per dollar of the insurer's total assets:

$$UCVOL_{i,t} = Std(\frac{UC_{i,t}}{TA_{i,t}}) = Std(UC^a_{i,t}) \tag{2}$$

where underwriting cash flow (*UC*) is the amount of cash generated from underwriting of an individual insurer, which is reported in the cash flow statement.[7] $UC^a_{i,t}$ is underwriting cash flow scaled by total assets. A common feature of the both operating risk measures is that they lump together different sources of insurer underwriting exposures in a single measure.

In testing the dynamic operating risk effect, we decompose the aggregate operating risk into i) a persistent component and ii) a transitory component. To conduct the decomposition, we follow Heaton and Lucas (1997) and assume that insurers' underwriting performance (i.e., underwriting income or underwriting cash flows) follows a first order auto-regressive model, i.e., an AR(1) process. Using the underwriting income (UI^a) measure as an example, we perform the following regression using underwriting income in the past 10 years for each individual firm i:

$$UI^a_{i,t-k} = \alpha_i + \beta^{UI^a}_{i,t} UI^a_{i,t-k-1} + \varepsilon_{i,t-k} \quad (k\ = 0\ through\ 9) \tag{3}$$

[6]Underwriting income is the net underwriting gain or loss reported in the statement of income of insurers' statutory annual statements. It is computed as the premiums earned deducting i) losses incurred, ii) loss expenses incurred, and iii) other underwriting expenses incurred.

[7]Reported in the cash flow statement of insurers' statutory annual statement, cash from underwriting is computed as premiums collected net of reinsurance net of loss and loss adjustment expenses paid and underwriting expenses paid, plus other underwriting incomes.

where $\beta_{i,t}^{UI^a}$ measures the level of persistence of the underwriting income shock.[8] A higher value of $\beta_{i,t}^{UI^a}$ indicates a more persistent shock, which is more difficult to smooth. Based on Equation (3), we decompose total underwriting risk to the variance of a permanent shock and the variance of a transitory shock. That is,

$$Var(UI_{i,t}^a) = \beta_{i,t}^2 Var(UI_{i,t-1}^a) + Var(\varepsilon_{i,t}) \tag{4}$$

Based on the variance decomposition of Equation (4), $\beta_{i,t}$**UIVOL* represents the permanent operating risk (*PBG*) and the standard deviation of $\varepsilon_{i,t}$ represents the transitory operating risk (*TBG*).

3.3. Credit Risk Measures

We evaluate credit risk exposure of property liability insurance companies based on the average credit ratings and credit spreads of insurers' corporate bond portfolios.

The first measure of credit risk taking is the average bond rating for an insurer's bond portfolio. The FISD database provides bond rating made by four rating agents: Duff & Phelps' rating, Fitch rating, Moody's rating, and S&P rating. While each rating agent uses its own scale system, there is a general consensus on the equivalent scale comparison. Based on the rating scale comparison, we convert the letter bond ratings into numerical rating scheme ranging from 3(D) to 27(AAA). A higher numerical rating indicates a lower credit risk exposure. The rating schemes of different rating agencies are provided in Appendix B. We primarily rely on the S&P rating in our analysis. Each year, we obtain the rating of a bond assigned by S&P closest to the year end. When an S&P rating is not available, Moody's rating, Fitch rating, and Duff & Phelps' rating (in this order) are alternatively used. With the credit rating of each corporate bond, we calculate the holding-weighted average of all corporate bond ratings as the credit rating of the portfolio held by an

[8]The mean of $\beta_{i,t}^{UI^a}$ across all sample firms is 0.24 with a standard deviation of 0.35. The mean and standard deviation of $\beta_{i,t}^{UI^a}$ are similar. To ensure stationarity, we exclude observations when the absolute values of their $\beta_{i,t}^{UI^a}$ and $\beta_{i,t}^{UC^a}$ are close to 1.

individual insurer.

$$Rating_{i,t} = \sum_{j=1}^{N_{i,t}} w_{i,j,t} * Rating_{j,t} \tag{5}$$

where $w_{i,j,t}$ is the portfolio weight of bond j in insurer i's corporate bond portfolio in year t; $N_{i,t}$ is the number of bonds in insurer i's corporate bond portfolio in year t; $Rating_{j,t}$ is the credit rating of bond j.

A major criticism on using ratings as credit risk measure is that ratings are updated slowly (Cornaggia and Cornaggia, 2011; Becker and Ivashina, 2012). Therefore, we consider yield spreads of insurer bond portfolios as the second credit risk measure. The estimation of portfolio yield spreads involves three steps. In the first step, we compute the yield of each bond held in the sample at the end of each year. Specifically, we estimate bond yield based on the following equation (Fabozzi 2003):

$$P_{j,t} = \sum_{j=1}^{N} \frac{C}{(1 + r_{j,t})^{\upsilon}(1 + r_{j,t})^{t-1}} + \frac{M}{(1 + r_{j,t})^{\upsilon}(1 + r_{j,t})^{n-1}} \tag{6}$$

where $P_{j,t}$ is the fair market value of the bond j at the end of year t.[9] υ is the ratio of days between year end and next coupon to days in a six-month period, C_j is the coupon payment, M_j is the face value of the bond, and n is the number of remaining coupon payment. $r_{j,t}$ is the yield to maturity of the bond during the 6-month period. We obtain the annualized yield of the bond by doubling $r_{j,t}$.

In the second step, following prior studies such as Collin-Dufresne and Goldstein (2001) and Campbell and Taksler (2003), we match each corporate bond with a treasury bond that has the closest remaining time to maturity. For the benchmark Treasuries, we use the CRSP Fixed Term indexes, which provide monthly yield data for notes and bonds of 1, 2, 5, 6, 10, 20, and 30 target years to maturity and use a linear interpolation scheme to estimate the entire yield curve. The credit spread is the yield to maturity on each bond in the sample and its spread over the closest

[9]The Schedule D data provides the fair market value for each holding in insurers' bond portfolios. For bond transactions, we use the actual costs (the buying price) and consideration (the selling price) for their fair market values.

benchmark U.S. treasury at the end of a year.

$$Spread_{j,t} = r_{j,t} - r_t^B \tag{7}$$

where $r_{j,t}$ is the estimated yield to maturity of corporate bond j at the end of year t, and r_t^B is the estimated yield to maturity of Treasury bond that at the end of year t.

In the third step, we compute the average yield spread of insurer i's corporate bond portfolio weighted by its portfolio holding:

$$Spread_{i,t} = \sum_{j=1}^{N_{i,t}} w_{i,j,t} * Spread_{j,t} \tag{8}$$

3.4. Other Variables

We cover a rich set of control variables to isolate for the influence of insurers' firm characteristics from the operating risk effect on insurers' credit risk taking. Larger firms and firms having longer history and having better underwriting performance, for instance, may have more rooms to absorb greater investment risks, thus diluting the impact of operating risks. We therefore include various firm characteristics, including,

- *LOGSIZE*: logarithm of the total book value of assets at the end of each year, obtained from insurers' balance sheets,
- *LOGAGE*: logarithm of firm age, computed as the difference between the reporting year and the year when the firm is founded,
- *PROFIT*: underwriting profit, measured as the ratio of an insurer's earned premiums to its incurred losses. Price index measures an insurer's profitability,
- *NONSTK*: dummy variable that equals one if an insurer is a mutual, reciprocal company, or affiliated with Llyods of London, and zero if it is a stock insurer, and

- *NONAFF*: indicator equal to one if an insurer is a stand-alone company (not affiliated with any insurance group or in a single-insurer group) and zero if it is affiliated with a group having more than one member firm.

An additional issue is that insurers face investment risks beyond credit risks. Naturally, the presence of other investment risk potentially has an influence on insurers' credit risk taking. We thus include the proxies for four alternative sources of investment risks in the regression: systematic risk of insurers' investments in common stocks, interest rate risk of insurers' Treasury bonds, agency bonds, and corporate bonds, percentage investment in government bonds, and percentage investment in stocks. Finally, insurers' organization may also affect their investment choice. To be specific, the following control variables are included:

- *DURATION*: Macaulay duration for an insurer's bond portfolio,
- *STKINV*: percentage of common stocks in total invested assets.[10] The inclusion of bond duration is to control for an insurer's interest rate risk,
- *BETA*: average beta of an insurer's equity portfolio weighted by year end's fair market value of each stock holding[11],
- *GOVINV*: ratio of investment in government bonds to total invested assets, and
- *STKINV*: ratio of investment in stocks to total invested assets.

3.5. Summary Statistics

Panel A of Table 2 shows the time-series averages of summary statistics for portfolio credit risk exposure, operating risk, and control variables for firms in our sample (with valid information from

[10] Schedule D, Part 1 of insurers' annual statements reports insurers' year-end positions in treasury bonds, agency bonds, and municipal bonds, in addition to corporate bonds (with details provided in Appendix A). We exclude structured bonds, callable, puttable, convertible, foreign, and euro bonds. We obtain bond features, such maturity and coupon information, from the Mergent FISD database.

[11] Common stock holding is from Schedule D, Part 2, Section 2 of insurers' annual statements reports. We use daily stock returns within a calendar year to estimate the year-end equity beta of a stock. To account for the effect of nonsynchronous trading, we estimate the market model for each using market returns up to five daily leads and five daily lags, in addition to the contemporaneous term. Following Dimson (1979), the stock beta is the sum of the estimated coefficients on the leads, lags, and the contemporaneous market returns.

NAIC and Mergent-FISD). For comparison purposes, we also report the summary statistics of the "universe" including all the property liability insurers in the NAIC database with positive surplus, losses and expenses and their assets exceeding USD1 million. The results for sample firms are reported in the first six columns and those for all NAIC insurers are reported in the subsequent 6 columns. For sample insurers, the time series average of cross-sectional means (medians) of portfolio ratings is 21.80 (22.02), corresponding to an S&P rating score of A-. This finding reflects that insurers as a group invest in relatively high-quality corporate bonds. Moreover, the mean (median) of credit spreads is 2.13% (1.95%) with a minimum of 0.92% and a maximum of 24.78%.[12]

In terms of operating risk, the mean *UIVOL* (*UCVOL*) for our sample insurers is 3.77% (7.27%). The mean *UIVOL* (*UCVOL*) for all insurers in the NAIC database is 4.62% (9.15%). Operating risk of sample firms appears to lower than that of all insurers. On average, sample firms are larger and exist longer than all NAIC firms – the average total assets for firms in the sample is USD 859.03 million while in PL insurer universe is USD 641.41 million; the average age of all NAIC firms is 44.72 years and the average age of sample insurers is 47.29 years. Moreover, Panel A shows that our sample firms resemble all NAIC firms in terms of firm profitability, equity beta, duration of bond portfolios, percentage investment in government bonds and stocks, and insurers' organization forms.

Panel B of Table 2 reports the correlations among insurers' credit risk, operating risk and other variables used in the analysis. The result shows that the two credit risk measures are inversely correlated. The correlation between bond portfolio rating and credit spread is -0.46, suggesting insurers of highly rated corporate bond portfolios have a low credit spread. Without any surprise, our two proxies for operating risk are highly positively correlated: the correlation between *UIVOL* and *UCVOL* is 0.70. The correlation between credit risk measures and operating risk proxies are in line with the operating risk hypothesis: the correlation between bond rating and *UIVOL* (*UCVOL*) is 0.20 (0.18) and the correlation between portfolio credit spread and *UIVOL* (*UCVOL*) is -0.15 (-0.16).

Some interesting results from the correlation table are worth noting. First, firm size is inversely

[12]Our main analysis includes bonds in all rating categories. We perform analysis with two alternative samples to ensure robustness. In the first alternative sample, we exclude AAA-rated bonds because the Mergent data for these bonds may contain errors (see, e.g., Elton et al., 2001; Campbell and Taksler, 2003). In the second alternative sample, we additionally exclude non-investment grade bonds. We obtain consistent results using the alternative samples.

correlated with bond ratings of insurer corporate bond portfolios, which might suggest that large insurers, perhaps less risk averse, tend to invest more in bonds with relatively lower ratings. Second, the correlations among the beta of the equity portfolio and credit risk measures, operating risk, and control variables are low. Insurers' investments in government bonds (*GOVINV*) are positively correlated with operating risk (the correlation is 0.17 for both operating risk measures) while the percentage investment in common stocks (*STKINV*) is negatively correlated with insurers' operating risk exposures (the correlation is -0.18 between *STKINV* and *UIVOL* and it is -0.24 between *STKINV* and *UCVOL*). Under the operating risk theory, greater operating risk results in lower investment risk. In this sense, the fact that *GOVINV* is positively correlated with operating risk but *STKINV* is negatively associated with operating risk is consistent with the operating risk effect theory.

4. Results

4.1. Static Operating Risk Effect

We first examine the static operating risk effect, the first hypothesis. That is, insurers' credit risk taking is inversely related to the aggregate operating risk exposure. We test this by looking at the average credit ratings and spreads across decile bond portfolios sorted by the aggregate operating risk measured by the volatility of insurers' underwriting income (*UIVOL*) and the volatility of insurers' underwriting cash flow (*UCVOL*). To do this, in each year we sort firms into deciles based on year t-1 *UIVOL* or *UCVOL* and compute the average rating and the average credit yield spreads of insurers in each decile group. In order to account for serial correlations across decile portfolio returns, we apply the Newey-West (1987) procedure with a 2-year lag when computing the t-statistics for the difference between the top (D10) and the bottom (D1) decile groups sorted by insurers' operating risk exposure in the prior year.

As illustrated in Table 3, there is a wide dispersion in operating risk exposure across different decile groups. When we sort insurers into decile groups based on *UIVOL*, the average *UIVOL* is 0.60% for D1 insurers while it is 12.06% for D10 insurers. Accordingly, the average corporate bond portfolio number rating for insurers in the D1 portfolio is 20.15 while that for D10 insurers is 22.88. The difference of 2.73 (t = 5.83) is significant at the 1 percent significance level. Note that the difference is economically significant as well: the rating score of 20 corresponds to a BBB+ rating for S&P and 23 corresponds to A+. The average holding for insurers in the lowest operating risk decile group is the medium investment grade while the average holding of insurers in the highest operating risk decile group is the upper medium grade. Moreover, the average yield spread for the D1 group is 2.54% while that for the D10 group is 2.05%. The difference of -0.49% in the yield spreads between D10 and D1 groups is significant at the 1 percent level. We obtain similar results when we sort insurers into decile groups based on *UCVOL*. Sorted by *UCVOL*, the difference in credit rating scores between the top and bottom decile portfolios is 2.48 with a t-statistic of 5.62 and the difference in yield spreads between these two groups is -0.54% with a t-statistic of -3.53. These findings are consistent with the static operating risk effect hypothesis.

Further, we perform panel regressions to examine the operating risk effect. The use of the regression analysis allows us to incorporate multiple variables thus we can address the potential effects of competing explanations for insurer credit risk taking. In the panel setting, we include fixed firm and time effects in the regression by including firm dummies and year dummies in the regressions. Considering the fact that our sample firms come from the same industry (i.e., the insurance industry) and that the variables included in the analysis are potentially stable over time, the regression residuals may be correlated across firms and over time. We follow Petersen (2006) to address the correlations of residuals using the two-way clustering method. The models are specified as following:

$$Rating_{i,t} = \alpha + \beta^1 \mathbf{X}_{i,t-1} + \mu_i^1 + v_t^1 + \varepsilon_{i,t}^1 \tag{9}$$

$$Spread_{i,t} = \alpha + \beta^2 \mathbf{X}_{i,t-1} + \mu_i^2 + v_t^2 + \varepsilon_{i,t}^2 \tag{10}$$

where Spread$_{i,t}$ and Rating$_{i,t}$ are the average yield spread and credit rating of the corporate bond portfolio of insurer i at the end of year t. X$_{i,t-1}$ is a vector of insurer i's operating risk measure and control variables in year t-1. Nine control variables are considered: the logarithm of firm size (*LOGSIZE*), the logarithm of firm age (*LOGAGE*), firm profitability (*PROFIT*), nonstock ownership (*NONSTK*), non-affiliated (*NONAFF*), duration of the bond portfolio (*DURATION*), beta of the equity portfolio (*BETA*), percentage investment in government bonds (*GOVINV*), and percentage investment in common stocks (*STKINV*). All are defined in section 3.4. μ_i^k (k=1,2) is a firm-specific intercept; υ_t^k (k=1,2) is the time-specific intercept. $\varepsilon_{i,t}^k$ (k=1,2) is a random error term assumed to be possibly heteroskedastic and correlated within firms and years.

In the first two columns of Table 4, we report the results for the panel regression analysis related to the static operating risk effect. Credit ratings are used as the proxy for credit risk taking in Panel A. Consistent with the sorted-portfolio result reported in Table 3, bond ratings are positively related with insurer operating risk. If we use *UIVOL* to measure operating risk (*BG*), the coefficient on *BG* is 1.72 (t = 3.93); alternatively if we use *UCVOL* as a *BG* measure, the regression coefficient on *BG* is 0.92 (t = 3.15). Both are significant at the 1% level. Panel B of Table 4 uses yield spreads as the dependent variable. Again, like the pattern revealed in Table 3, we find that insurers' operating risk is negatively related to yield spreads of insurers' corporate bond portfolios. The coefficients on *UIVOL* and *UCVOL* are -0.73 (t = -2.33) and -0.53 (t = -2.32) respectively. Taken together, the evidence indicates that operating risk has significant influence on insurer credit risk taking, even after controlling for insurer characteristics and other investment risks taken by insurers.

Besides the key results on operating risk, our analysis reveals interesting patterns in insurers' portfolio decisions. First, *DURATION* is negatively related to bond ratings while positively related to portfolio yield spreads. Durations measure the interest rate risk exposure. Thus the result indicates that insurers taking greater credit risk exposure simultaneously expose to greater interest rate risk. Second, the fractional stock investment (*STKINV*) is negatively related to credit rating and positively related to yield spread. That is, insurers investing more in stocks would take greater credit risk in corporate bonds. It appears that insurers have their "taste" in risk taking; insurers' pick in credit risk exposure is aligned with their investments in alternative risk exposures.

4.2. Intertemporal Smoothing - Dynamic Operating Risk Effect

4.2.1. Permanent Shocks versus Transitory Shocks

Not all operating risks would affect asset allocation in the same way when the dynamic effect is considered. In the dynamic setting, the aggregate operating risk can be decomposed into persistent and transitory components. Our second hypothesis states that the persistent operating risk has a greater effect on insurers' credit risk taking than transitory operating risk does. We perform analysis to differentiate the influences of the two types of operating risk. The result is reported in the last two columns of Table 4.

Reported in Panel A of Table 4 (the dependent variable is bond rating), the coefficient on persistent operating risk (*PBG*) is 2.71 (t = 4.64) when measuring operating risk using *UIVOL*; the coefficient on *PBG* is 1.40 (t = 4.44). By contrast, the coefficient on *TBG* is merely 0.45 with a t-statistic of 1.73 when we measure operating risk with *UIVOL*; the coefficient on *PBG* is 0.29 with a t-statistic of 1.55 when we measure operating risk with *UCVOL*. Both the magnitude and t-statistics for *PBG* is much larger than for *TBG*, which suggests the permanent operating risk is a more important determinant of insurers' credit risk taking than the transitory operating risk.

In Panel B, we use yield spreads as the dependent variables. The results are consistent with what we find in Panel A. To be specific, the coefficient on persistent operating risk (*PBG*) is -2.28 (t = -2.56) when measuring operating risk using *UIVOL*; the coefficient on *PBG* is -1.77 (t = -2.85). By contrast, the coefficient on *TBG* is merely -0.56 with a t-statistic of -1.83 when we measure operating risk with *UIVOL*; the coefficient on *PBG* is -0.43 with a t-statistic of -1.69 when we measure operating risk with *UCVOL*. Our findings support the hypothesis that persistent shocks have a greater impact on insurers' credit risk taking.

4.2.2. Evidence on Financial Constraint Effect

Now we examine the last testable implication of the operating risk effect regarding the impact of financial constraints. The specific hypothesis is that insurers with greater financial constraints have poorer ability to smooth the transitory operating risk, therefore, their credit risk taking would be more sensitive to the transitory operating risk.

A popular measure is the KZ index advocated by Kaplan and Zingales (1997), Lamont, Polk and Saa-Requejo (2001) and Baker, Stein, and Wurgler (2003). However, the KZ index is developed for industrial firms. We suspect that financial institutions, such as insurance firms, have different relationship between accounting variables and their financial status. As a result, the KZ index is not applicable to our study. We use three proxies for financing constraints. The first is based on firm size. The role of firm size is similar to the wealth effect on individuals' investment. Just as wealthy individuals have more money to invest and they may invest more in risky assets, large firms have more to invest and may prefer to take riskier investments. We construct a dummy variable, *SMALL*, that equals one for the bottom quintile insurers sorted by book total assets and zero for other quintiles. We expect small firms to have more financial constraints and the operating risk effect on bond portfolio credit risk is stronger.

The second financial constraint measure is the ownership structure of insurance firms. Lamm-Tennant and Starks (1993) find that stock insurers have a better access to the capital market relative to mutual insurers. Similarly, Harrington and Niehaus (2002) present evidence that mutual insurers have higher ex ante target capital to liability ratios than stock insurers. In addition, the capital to liability ratio is more sensitive to income for mutual insurers than for stock insurers. Enlightened by these findings, we hypothesize that stock insurers have less financing constraints than mutual insurers. We construct a dummy variable *NONSTK* to proxy for ownership structure. *NONSTK* equals one for mutual insurers and zero for stock insurers.

The third proxy for financing constraint is group affiliation. An insurance company can be a stand-alone firm or a member of a conglomerate group. Insurers affiliated with a conglomerate group are more likely to have access to the internal capital market of the conglomerate, which helps reduce external financing constraints. We construct a dummy variable, *NONAFF*, to proxy the status of affiliation. *NONAFF* equals one for stand-alone insurers and zero otherwise.

The results using *UIVOL* as the measure of aggregate operating risk are reported in the first three columns of Table 5 while those using *UCVOL* as the aggregate operating risk measure are reported in the last three columns. As the hypothesis is on insurers' portfolio responses to transitory operating risk, we include *TBG* in the analysis. Panel A shows that firm size and affiliation have significant impact on the relationship between operating risk and credit rating. The coefficient on *TBG* and *SMALL* is 0.17 (t = 2.06) and the coefficient on *TBG*NONAFF* is 0.34 (t = 1.87). That is, the effect of transitory operating risk on credit rating is stronger for small firms and non-affiliated firms. However, there is no evidence that stock ownership makes a difference in the role of transitory operating risk on insurers' credit risk taking.[13]

Moreover, Panel B shows that firm size and affiliation have a significant impact on the relationship between transitory operating risk and yield spreads of insurers' corporate bond portfolios. We find that the coefficients on the product terms between *TBG* and firm size and between *TBG* and *NONAFF* are both significantly negative, suggesting that among small firms or non-affiliated insurers, insurers with greater transitory operating risk are inclined to hold corporate bonds with relatively smaller yield spreads. Again, we do not have evidence that ownership structure affects operating risk effect. We conclude that the findings present a modest support to the financial constraint effect hypothesis.

4.3. Alternative Operating Risk Measures

In this section, we perform a robustness check by using alternative operating risk measures to test the operating risk theory. Four firm attributes reflecting the level of an insurer's operating risk taking are used to measure an insurer's operating risk exposure. As all these measures are highly persistent over time (e.g., firm leverage ratio does not change much over time), we only test the static operating risk effect.

The first alternative operating risk measure is an insurer's leverage ratio (*LEVERAGE*). It is calculated as the ratio of an insurer's total liabilities to its total assets. Both items are from the balance sheet of the NAIC database. Insurers rarely issue bonds to raise capital. As a result, the leverage ratio of insurers is different from the financial leverage of industrial firms. For insurers, their leverages are mainly determined by claim liabilities (i.e., claim costs to be paid in the future). In this way, high leverage reflects greater operating risk exposure.

The second alternative measure, *LONG*, is the fraction of premium income from long "tailed" insurance business in an insurer's aggregate premium income. The so-called claim tail measures

[13] Although insurers with mutual ownership are perceived as having more difficulty accessing the capital market than do stock insurers, a recent study by Berry-Stolzle, Nini and Wende (2012) shows that mutual insurers have access to capital markets by issuing surplus notes. Therefore, the mutual status may not be a good proxy for financing constraint.

the average payment horizon of an insurer's future claim liabilities after the insurance policies are issued. Insurer with relatively longer claim tails are engaged in more operating risk. As a result, there is a greater operating risk exposure for their credit risk taking. Following the conventional practice, we consider a number of business sectors as long-horizon business lines including i) auto liability, ii) general liability, iii) farm and homeowners insurance, iv) commercial multiple perils, v) medical malpractice liability, vi) workers' compensation, vii) aircraft insurance, and viii) boiler and machinery insurance.

The third and fourth alternative measures are an insurer's concentration, i.e., the lack of diversifications, across business lines (*HERFL*) and across states (*HERFS*). We expect insurers with greater concentration in insurance operations to face greater operating risk.

To be specific, *HERFL* is the sum of squared ratio of written premium in a business line of an insurer to the total written premium by the insurer. That is,

$$HERFL_{it} = \sum_{j=1}^{N_i} (\frac{PREM_{ijt}}{TPREM_{it}})^2 \tag{11}$$

where *PREM*$_{ijt}$ is the premium written of insurer *i* in line (segment) *j* and year *t*, and *TPREM*$_{it}$ is the total premiums by insurer *i* in year *t*. N_i is the maximum line of insurer *i*. Data for written premiums across different business lines are Part 1B of the Underwriting and Investment Exhibit of Insurers' annual statements provided by NAIC. We follow the Best Average and Aggregates to classify business.

Moreover, *HERFS* is evaluated as the sum of the squared percentages of insurance premiums written in each state to the total premiums written in all states by an insurer:

$$HERFS_{it} = \sum_{s=1}^{50} (\frac{PREM_{ist}}{TPREM_{it}})^2 \tag{12}$$

where *PREM*$_{is}$ is premiums written in state s (s=1, 2, ..., 50) of insurer *i*, and *TPREM*$_{it}$ is total premium written across all sates.

With these alternative operating risk measures, we examine the effect of operating risk effect on insurers' credit risk taking and report the results in Table 6. We find that firm size, long tail business, and business-line diversification has significant impact on both credit ratings and yield spreads. For instance, the coefficient on leverage is 0.45 (t = 2.65) in the credit rating regression while the coefficient is -0.25 (t = -2.11) in the yield spread regression. The untabulated analysis shows that low correlations among the four proxies. We therefore include all of them in the regression, reported in the last column, and find that the coefficients on leverage, long claim horizon, and Herfindale index of business lines are significant in the rating regressions; in the yield spread regressions, we find that the coefficients on leverage and long tail are significant. In sum, these alternative operating risk proxies potentially capture different aspects of insurers' operating risk. The operating risk theory holds when these alternative proxies are employed to measure operating risk.

5. Operating Risk and Investment Performance Relation in the Period of Financial Crisis

The prediction of the background risk effect is that the presence of background risk makes investors act conservatively in investments. As such, the recent financial crisis presents a window to further test the potential background risk effect. There is pervasive evidence that credit risk is negatively related to cross-sectional financial and operating performance (e.g., Dichev, 1998; Campbell, Hilscher, and Szilagyi, 2005). Avramov, Chordia, Jostova, and Philipov (2009) show that the negative relation between credit risk and performance holds only in periods of bad credit conditions with wide spreading rating downgrades. Consequently, we expect that firms exposed more to credit risk would incur greater investment losses during the financial crisis than those less exposed. Together with the background risk effect, we hypothesize that, during the financial crisis, high background risk firms would incur less investment losses than low background risk firms.

We perform panel regressions to explore the hypothesized relationship between insurers' operating risk and their investment performance. In the analysis, we quantify insurers' investment performance with the ratio of the aggregate investment income and capital gain reported at the year beginning to invested assets reported at the year end. The two investment performance elements, net investment income and capital gains, are reported in the Exhibits of Net Investment Income and Capital Gains, available from the NAIC database. To see the role of the financial crisis, we construct a *NONCRISIS* dummy, equal to zero from 2007 to 2009 and one otherwise, and interact it with background risk measures. Based on this design, the coefficients on the operating risk measures, *UIVOL* or *UCVOL*, capture the relation between background risk and insurers' investment performance during the crisis. The coefficients on the interaction, $UIVOL * NONCRISIS$ stands for the the differential effects in the non-crisis period and the crisis period. Consistent with regressions in prior sections, the regression includes firm size, firm age, the group dummy, and the stock ownership dummy as control variables and considers firm fixed effects.

The empirical results are reported in Table 7. The first column shows the result when *UIVOL* is used to gauge background risk. The coefficient on *UIVOL* is 2.98 (t=3.29), indicating a significant positive relationship between background risk and investment performance in the crisis period. Moreover, the coefficient on $UIVOL * NONCRISIS$ is -2.70 (t=-3.39), suggesting a significant difference in the background risk effect on investment performance between the crisis and non-crisis periods. We obtain similar results when other background risk measures are used. The evidence support that insurers exposed to higher background risk suffer less in their investment performance during the recent financial crisis. Further in Table 7 (Columns 3 and 4), we report the findings for the regressions on the dynamic background risk effect, where both permanent and transitory background risk components are considered. Only the permanent background risk plays a significant in determining insurers' investment performance in the crisis period. Reported in Column (3) where UIVOL is the background risk measure, the coefficients on PBG and TBG are respectively 2.58 (t=4.12) and 0.34 (t = 0.72). This again is aligned with the background risk theory that the permanent background risk has a stronger effect in affecting insurers' credit risk taking than does the transitory background risk.

A further interesting observation is that the magnitude of the coefficients on background risk measures are low in the normal (non-crisis) time. Based on the result reported in the first two columns, the coefficients on *UIVOL* and *UCVOL* in the normal time are 0.28 (= 2.98-2.70) and 0.70 (2.90-2.20), respectively. Our findings suggest that background risk on investment performance is weak in the non-crisis period, i.e., the risks from various market segments are unrelated during "normal times", while the dependency is much stronger in the extreme market conditions.

6. Conclusions

Insurance companies hold a substantial stake in the corporate credit market. This study presents empirical evidence on an important economic prediction that variability of insurers' underwriting business, which is typically uncorrelated with risks of insurers' investment portfolios, affects insurers' credit risk taking behavior. Using data on property and liability insurance firms for the period between 1996 and 2010, we present evidence that that insurers facing greater operating risk take less credit risk. Moreover, consistent with the dynamic version of the operating risk theory, insurers with more persistent underwriting income/cashflow shocks are less aggressive in credit risk taking. We also show that transitory operating risk has a significant role in determining credit risk taking for insurers with tight financing constraints.

Recognizing the fact that operating risk takes effect among institutional investors is important. operating risk is potentially a mechanism for the inter-connection among various sectors of the financial market, and especially for strong downside correlations among various financial businesses. This can be understood in light of recent turmoil in the financial markets, when financial institutions rush to unwind risk-taking behavior in one corner of the industry when they face heightened risk in another corner, even though during "normal periods" of time the performance of such business are much uncorrelated.

Appendices

A. Bond Classifications by Schedule D

We obtain property/liability insurers' corporate bond holding information from Schedule D of the National Association of Insurance Commissioners data (NAIC data). Schedule D classifies bonds into eight different types based on the nature of issuer:

- Government bonds, including US Government bonds and Other Government bonds
- States, Territories and Possessions bonds
- Political Subdivisions of States, Territories and Possessions bonds
- Special Revenue, Special Assessment Obligations of agencies and authorities of governments and their political subdivisions bonds
- Unaffiliated Public Utilities bonds,
- Unaffiliated Industrial and Miscellaneous bonds,
- Credit Tenant Loans, and,
- Parent, Subsidiaries and Affiliates Bonds.

For each bond category, Schedule D future provides four sub-classifications based on the nature of bonds:

- Bonds not backed by other loans. These are bonds without collateral or with non-financial assets as collateral.
- Loan-backed bonds. These are asset backed bonds that are backed by loans other than mortgages, such as home equity loans, auto loans, credit card receivables, student loans, and other loans.
- Collateralized mortgage obligations. These are bonds backed by mortgages.
- Other structured securities. These are other types of structured securities that do not belong to asset-backed bonds or collateralized mortgage obligations.

We use the following procedures to select our sample corporate bonds:

- Choose unaffiliated public utilities, unaffiliated industrial and miscellaneous bonds as our initial corporate bonds sample;
- Only include "bonds not backed by other loans" from the four types of different loans. The reason is that the other three kinds of bonds are structured bonds whose pricing is complicated and whose risk is difficult to evaluate;
- Require sample bonds to have positive face value and fair value;
- Exclude observations with obvious error in CUSIP.

This results in a clean sample of 57,535 unique corporate bond issues from the NAIC Schedule D database.

B. Corporate Bond Ratings

The following table summarizes rating grades of four rating agencies, S&P, Moody's, Fitch, and Duff & Phelps and the associated number ratings used in the analysis. The rating scheme here inverts the number ratings provided in the Mergent FISD database.

Number Rating	**S&P**	**Moody's**	**Fitch**	**Duff & Phelps**
27	AAA	Aaa	AAA	AAA
26	AA+	Aa1	AA+	AA+
25	AA	Aa2	AA	AA
24	AA-	AA3	AA-	AA-
23	A+	A1	A+	A+
22	A	A2	A	A
21	A-	A3	A-	A-
20	BBB+	Baa1	BBB+	BBB+
19	BBB	Baa2	BBB	BBB
18	BBB-	Baa3	BBB-	BBB-
17	BB+	Ba1	BB+	BB+
16	BB	Ba2	BB	BB
15	BB-	Ba3	BB-	BB-
14	B+	B1	B+	B+
13	B	B2	B	B
12	B-	B3	B-	B-
11	CCC+	Caa1	CCC+	
10	CCC	Caa2	CCC	CCC
9	CCC-	Caa3	CCC-	
8	CC	Ca	CC	
7	C	C	C	
6			DDD	
5			DD	DD
4			D	
3	D		D	
2	SUSP	SUSP	SUSP	SUSP
1	NR	NR	NR	NR

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Table 1: Bond Sample Selection Procedure and Summary Statistics

This table presents the procedure to construct the corporate bond sample and the by-year statistics of corporate bond characteristics. Panel A presents the steps to obtain our corporate bond sample. It begins with corporate bond holding data from Schedule D of National Association of Insurance Commissioners (NAIC) annual statement database. Bond holding with missing or zero par value and non-positive market value are removed. The bond holding is further merged with corporate bonds included in the Mergent FISD database. Bonds with credit enhancement, with asset-backed feature, Yankee bonds, Canadian bonds, and bonds in foreign currency are deleted. The number of bond issues in panel A is to count the distinct bonds in the sample period. Panel B presents the characteristics of the corporate bond in respective sample years and throughout the entire sample period. It includes i) the number of distinct bonds, ii) the number of distinct bonds per insurer, iii) the aggregate market value of bonds in our sample, iv) the fraction of investment grade bonds (%), v) the fraction of bonds with maturity shorter than 5 years (%), vi) the fraction of bonds with maturity between 5 and 10 years (%), and vii) the fraction of bonds with time to maturity longer than 10 years (%). All the percentages are computed in terms of market value. For the all-year statistics, the number of bonds is the number of unique bond issues over the sample period. The rest statistics are the average of the numbers over time. The sample period is from 1996 to 2010.

Panel A: Procedure to Construct Corporate Bond Sample

	Number of Bonds
Bonds after merging with the FISD data	46,247
Final sample of Fixed-rate US dollar bonds (noncallable, nonputtable, nonsinking fund, nonconvertible, non-asset-backed, non-credit enhancement, and non-AAA-rated)	30,436

Panel B: Corporate Bond Characteristics in Sample Years

Year	# of Bonds	# of Bonds Per Insurer	Bond Value (Billion)	% in Investment Grade	$\% \leq 5$ years	$5 < \% < 10$ years	$\% \geq 10$ years
1996	5,398	21	66.42	96.28	36.20	50.56	13.24
1997	6,104	22	72.78	96.45	39.23	48.65	12.12
1998	6,742	23	79.21	96.42	42.86	44.79	12.35
1999	7,202	24	83.05	95.88	44.61	43.58	11.81
2000	7,113	26	86.68	96.52	50.03	39.09	10.88
2001	7,078	28	97.05	95.64	47.35	41.47	11.19
2002	6,862	31	98.30	94.62	46.60	42.06	11.33
2003	6,488	36	86.41	94.22	45.27	41.61	13.11
2004	6,623	36	108.23	95.51	47.48	40.94	11.57
2005	6,227	35	103.23	95.12	52.19	38.58	9.23
2006	6,036	35	104.41	95.21	53.51	36.72	9.77
2007	5,943	34	102.86	94.84	55.60	35.66	8.74
2008	5,705	34	97.27	96.33	58.23	34.50	7.26
2009	5,833	34	99.76	98.75	57.37	35.06	7.11
Total/Average	9,528	42	91.22	95.62	47.63	41.40	10.97

Table 2: Summary Statistics of Insurer Characteristics

Panel A of this table reports summary statistics of all insurers covered in the NAIC property-liability database (All Insurers) and insurers included in our sample that report their financial data and corporate bond holding (In-sample Insurers). The time-series averages of cross sectional statistics, including number of observations, mean, median, standard deviations, minimum, and maximum. $RATING$ is the bond market value weighted average ratings of an insurer's corporate bond portfolio. $SPREAD$ is the market value weighted average yield spread (the difference in the yields between the corporate bond held by an insurer and the corresponding treasury bond) of an insurer's corporate bond portfolio. $UIVOL$ is the standard deviation of the ratios of net underwriting gain (loss) to invested assets in the prior 10 years. $UCVOL$ is the standard deviation of the ratios of cash flow from underwriting to invested assets in the prior 10 years. $SIZE$ (in million dollars) is the book value of firms assets at the year end. AGE (firm age) is computed as the difference between the year of reporting and the firm incorporation year. $PROFIT$ is the ratio of an insurer's earned premiums to incurred losses. $BETA$ is the holding-weighted averaged beta for stocks held by each sample insurer. $DURATION$ is the bond market value weighted average of durations of all government and corporate bonds held by each sample insurer. Panel B of the table reports the correlations among the variables. The sample period is from 1996 to 2010.

Panel A: Summary Statistics

	Sample Firms						**All NAIC Insurers**					
	N	Mean	Median	Std	Min	Max	N	Mean	Median	Std	Min	Max
						Credit Risk Measures of Insurers Corporate Bond Portfolios						
RATING	1,134	21.80	22.02	1.34	12.48	25.03	–	–	–	–	–	–
SPREAD (%)	1,134	2.13	1.95	1.16	0.92	24.78	–	–	–	–	–	–
						Operating Risk Measures						
UIVOL (%)	1,134	3.77	2.74	3.45	0.54	17.75	1,819	4.62	3.09	4.39	0.54	17.75
UCVOL (%)	1,134	7.27	4.96	7.12	1.06	36.85	1,819	9.15	5.7	9.25	1.06	36.85
						Control Variables						
SIZE	1,083	859.03	125.18	3,632.39	2.07	79,616.95	1,710	641.41	73.58	3,113.72	1.25	79,616.95
AGE	1,005	47.29	29.09	41.6	2.64	209.45	1,596	44.72	27.27	40.75	1	209.45
PROFIT	1,007	1.50	1.41	0.53	0.54	4.9	1,509	1.54	1.42	0.57	0.52	4.94
NONSTK	1,083	0.35	0.08	0.42	0.08	1.00	1,710	0.34	0.08	0.41	0.08	1.00
NONAFF	1,083	0.29	0	0.45	0	1.00	1,710	0.33	0	0.47	0	1.00
DURATION	1,073	4.36	4.18	1.51	0.85	12.43	1,446	4.26	4.04	1.75	0.44	14.55
BETA	621	0.89	0.90	0.32	-0.48	3.13	854	0.87	0.89	0.33	-0.55	3.18
GOVINV	1,083	0.18	0.14	0.15	0	0.84	1,708	0.22	0.16	0.21	0	0.99
STKINV	1,083	0.14	0.10	0.15	0	0.85	1,709	0.14	0.08	0.17	0	0.93

Panel B: Correlations among Variables

	RATING	SPREAD	UIVOL	UCVOL	SIZE	AGE	PROFIT	NONSTK	NONAFF	DURATION	BETA	GOVINV
PREAD	-0.56											
UIVOL	0.20	-0.15										
UCVOL	0.18	-0.16	0.70									
SIZE	-0.15	0.08	-0.18	-0.17								
AGE	-0.02	0.02	-0.09	-0.17	0.13							
PROFIT	0.01	0.04	0.04	0.00	-0.06	-0.03						
NONSTK	0.13	-0.06	-0.04	-0.16	0.00	0.38	-0.03					
NONAFF	0.15	-0.03	0.11	0.00	-0.12	-0.01	0.11	0.31				
DURATION	-0.19	-0.02	-0.17	-0.18	0.09	0.06	-0.06	0.03	-0.05			
BETA	0.01	-0.02	-0.01	0.00	0.02	-0.02	-0.01	0.05	0.06	0.03		
GOVINV	0.20	-0.10	0.17	0.17	-0.12	-0.08	-0.01	0.01	0.16	-0.02	0.01	
STKINV	-0.15	0.12	-0.18	-0.24	0.20	0.32	0.02	0.22	-0.03	0.12	0.00	-0.24

Table 3: Credit Risk Exposure across Insurers' Aggregate Operating Risk Decile Groups

This table reports the averages of bond portfolio ratings and credit spreads (in percentage points) in tandem with operating exposure in the prior year. The operating risk measures are sorted into decile groups in each year. UIVOL is the standard deviation of the ratios of net underwriting gain (loss) to invested assets in the prior 10 years. UCVOL is the standard deviation of the ratios of cash flow from underwriting to invested assets in the prior 10 years. We first compute the average portfolio rating and credit spread for each decile group in each year, then average the portfolio averages across the entire sample period. The differences of portfolio rating and credit spread between the top (D10) and bottom (D1) portfolio deciles are reported. Inside the parentheses are the Newey-West (1987) adjusted t-statistics with a 2-year lag. The sample period is from 1996 to 2010.

	Sorted by UIVOL			Sorted by UCVOL		
Rank	UIVOL (%)	RATING	SPREAD (%)	UCVOL (%)	RATING	SPREAD (%)
D1	0.60	20.15	2.54	1.15	20.32	2.60
2	1.09	20.30	2.40	2.04	20.51	2.48
3	1.56	20.75	2.25	2.84	20.70	2.29
4	2.00	21.04	2.20	3.62	21.02	2.22
5	2.46	21.86	2.14	4.45	21.64	2.16
6	2.99	21.85	2.18	5.46	21.88	2.13
7	3.67	21.95	2.16	6.79	21.85	2.16
8	4.60	21.90	2.14	8.76	21.88	2.17
9	6.20	22.12	2.18	12.28	22.27	2.17
D10	12.06	22.88	2.05	25.11	22.80	2.06
D10-D1		2.73***	-0.49***		2.48***	-0.54***
(t-stat)		(5.83)	(-3.25)		(5.62)	(-3.53)

Table 4: Panel Regressions of Portfolio Credit Risk Taking on Insurers' Operating Risk

This table reports the results of panel regressions of portfolio credit risk measures on insurers' operating risk. BG is the measure of operating risk (UIVOL or UCVOL). UIVOL is the standard deviation of the ratios of net underwriting gain (loss) to invested assets in the prior 10 years. UCVOL is the standard deviation of the ratios of cash flow from underwriting to invested assets in the prior 10 years. Persistent operating risk (PBG) is measured as $\beta_{i,t}^{UI}$*UIVOL or $\beta_{i,t}^{UI}$*UCVOL, where $\beta_{i,t}^{UI}$ is estimated from the AR(1) regressions using data from year t-9 through t for firm i: $UI_{i,t-k} = \alpha_i + \beta_{i,t}^{UI} UI_{i,t-k-1} + \varepsilon_{i,t-k}$ $(k = 0\ through\ 9)$. TBG is the standard deviation of the residual of the regression. LOGSIZE is the logarithm of the book value of firms assets at the year end. LOGAGE is the logarithm of firm age, which is computed as the difference between the year of reporting and the firm incorporation year. PROFIT is the ratio of an insurer's earned premiums to incurred losses. NONSTK is a dummy variable that equals one if an insurer is a mutual, reciprocal company, or affiliated with Llyods of London, and zero if it is a stock insurer. NON-AFF is an indicator equal to one if an insurer is a stand-alone company (not affiliated with any insurance group or in a single-insurer group) and zero if it is affiliated with a group having more than one member firm. DURATION is the bond market value weighted average of durations of all government and corporate bonds held by each sample insurer. BETA is the holding-weighted averaged beta for stocks held by each sample insurer. GOVINV is the ratio of investment in government bonds to total invested assets. STKINV is the ratio of investment in stocks to total invested assets. We use fixed firm and fixed time effects model assuming cross-sectional and time-series correlations in the residual terms. We report results using ratings as the dependent variable in Panel A and yield spread in Panel B. The t-statistics (adjusting for the firm and year two-way clustering) are reported in the parentheses. The sample period is from 1996 to 2010. Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Panel A: Measuring Credit Risk using Average Ratings of Bond Portfolios

	Static Operating Risk Effect		Dynamic Operating Risk Effect	
	UIVOL	UCVOL	UIVOL	UCVOL
INTERCEPT	20.75***	20.67***	20.85***	20.62***
	(47.23)	(43.21)	(43.17)	(43.11)
BG	1.72***	0.92***		
	(3.93)	(3.15)		
PBG			2.71***	1.40***
			(4.64)	(4.44)
TBG			0.45*	0.29
			(1.73)	(1.55)
LOGSIZE	0.06	0.07	0.05	0.04
	(0.99)	(1.12)	(0.74)	(0.82)
LOGAGE	0.11	0.11	0.11	0.11
	(0.82)	(0.84)	(0.80)	(0.80)
PROFIT	-0.05	-0.05	-0.04	-0.05
	(-1.05)	(-1.05)	(-1.01)	(-1.02)
NONSTK	0.23	0.24	0.23	0.24
	(1.40)	(1.41)	(1.40)	(1.41)
NONAFF	-0.11	-0.10	-0.11	-0.10
	(-1.27)	(-1.24)	(-1.28)	(-1.21)
DURATION	-0.04**	-0.03**	-0.04**	-0.03**
	(-2.03)	(-2.00)	(-2.02)	(-2.00)
BETA	0.02	0.03	0.02	0.03
	(0.45)	(0.43)	(0.53)	(0.56)
GOVINV	0.25	0.25	0.25	0.25
	(1.47)	(1.46)	(1.50)	(1.55)
STKINV	-0.63**	-0.63**	-0.63**	-0.63**
	(-2.11)	(-2.09)	(-2.12)	(-2.04)
Firm and Year Dummies	Yes	Yes	Yes	Yes
N	9,154	9,154	9,154	9,154
Adjusted R^2	0.65	0.65	0.68	0.68

Panel B: Measuring Credit Risk using Average Credit Spreads of Bond Portfolios

	Static Operating Risk Effect		Dynamic Operating Risk Effect	
	UIVOL	UCVOL	UIVOL	UCVOL
INTERCEPT	2.39***	2.26***	2.69***	2.57***
	(8.15)	(9.19)	(8.93)	(9.14)
BG	-0.73**	-0.53**		
	(-2.33)	(-2.32)		
PBG			-2.28***	-1.77***
			(-2.56)	(-2.85)
IBG			-0.56*	-0.43*
			(-1.83)	(-1.69)
LOGSIZE	-0.04	-0.02	-0.01	-0.01
	(-0.82)	(-0.93)	(-0.86)	(-0.73)
LOGAGE	0.14	0.13	0.11	0.12
	(1.61)	(1.49)	(1.59)	(1.52)
PROFIT	0.01	0.03	0.04	0.04
	(0.32)	(0.55)	(0.54)	(0.54)
NONSTK	-0.24*	-0.23**	-0.21**	-0.22**
	(-1.87)	(-2.37)	(-2.43)	(-2.50)
NONAFF	0.05	0.04	0.03	0.03
	(0.91)	(1.18)	(1.01)	(1.08)
DURATION	0.05**	0.04**	0.05**	0.05**
	(2.27)	(2.15)	(2.18)	(2.09)
BETA	0.01	0.01	0.02	0.02
	(0.16)	(0.09)	(0.18)	(0.12)
GOVINV	0.01	0.02	0.03	0.04
	(0.06)	(0.27)	(0.14)	(0.47)
STKINV	0.82**	0.67***	0.65***	0.65***
	(2.41)	(3.42)	(3.26)	(3.31)
Firm and Year Dummies	Yes	Yes	Yes	Yes
N	9,154	9,154	9,154	9,154
Adjusted R^2	0.54	0.55	0.59	0.59

Table 5: Financing Constraints and Transitory Operating Risk Effect

This table reports the coefficients of panel regressions of bond portfolio credit risk on insurer operating risk and financing constraints. The specific model is a fixed firm and fixed time effects model assuming cross-sectional and time-series correlations in the residual terms (Petersen, 2009). Credit risk measures, operating risk measures, and control variables are defined in the same way as in Table 4. TBG is the standard deviation of the residual of the regression: $UI_{i,t-k} = \alpha_i + \beta_{i,t}^{UI} UI_{i,t-k-1} + \varepsilon_{i,t-k}$ $(k = 0\ through\ 9)$. We use three dummy variables to measure firm financing constraints. SMALL is a dummy variable that equals one for the bottom quintile insurers sorted by total book assets and 0 for other quintiles. NONSTK is a dummy variable which equals one for mutual insurers and 0 otherwise. NONAFF is a dummy variable which equals one for stand-alone insurers and 0 otherwise. Panel A reports results when credit ratings are used as the dependent variable. Panel B reports results when credit spreads are the dependent variable. The t-statistics (adjusting for the firm and year two-way clustering) are reported in the parentheses. The sample period is from 1996 to 2010. Note: *** p<0.01, ** p<0.05, * p<0.10.

Panel A: Measuring Credit Risk Using Bond Credit Ratings

	UIVOL as Operating Risk Measure			UCVOL as Operating Risk Measure		
	(1)	(2)	(3)	(4)	(5)	(6)
INTERCEPT	20.76***	20.74***	20.77***	22.73***	22.69***	22.63***
	(47.03)	(46.77)	(47.18)	(47.48)	(46.48)	(47.89)
TBG	0.58	0.38	0.46	0.53	0.51	0.48
	(0.89)	(0.61)	(0.84)	(0.88)	(0.80)	(0.68)
TBG*SMALL	0.17**			0.24**		
	(2.06)			(2.27)		
TBG*NONSTK		0.21			0.27	
		(1.26)			(1.10)	
TBG*NONAFF			0.34*			0.22*
			(1.87)			(1.94)
LOGSIZE	0.07	0.06	0.06	0.06	0.06	0.06
	(1.09)	(1.00)	(0.88)	(1.01)	(1.09)	(1.02)
LOGAGE	0.11	0.11	0.12	0.12	0.12	0.02
	(0.83)	(0.80)	(0.85)	(0.73)	(0.64)	(0.61)
PROFIT	-0.05	-0.05	-0.05	-0.04	-0.04	-0.04
	(-1.06)	(-1.05)	(-1.04)	(-1.30)	(-1.21)	(-1.26)
NONSTK	0.24	0.26	0.23	0.25	0.25	0.26
	(1.47)	(1.35)	(1.38)	(1.42)	(1.32)	(1.26)
NONAFF	-0.11	-0.11	-0.19	-0.12	-0.13	-0.11
	(-1.29)	(-1.27)	(-1.56)	(-1.25)	(-1.27)	(-1.62)
DURATION	-0.04**	-0.04**	-0.04**	-0.05**	-0.05**	-0.05**
	(-2.05)	(-2.03)	(-2.04)	(-2.25)	(-2.51)	(-2.36)
BETA	0.02	0.02	0.02	0.02	0.02	0.02
	(0.41)	(0.45)	(0.39)	(0.60)	(0.54)	(0.57)
GOVINV	0.25	0.25	0.26	0.26	0.24	0.26
	(1.51)	(1.48)	(1.53)	(1.58)	(1.51)	(1.53)
STKINV	-0.62**	-0.63**	-0.63**	-0.63**	-0.63**	-0.63**
	(-2.09)	(-2.11)	(-2.10)	(-2.55)	(-2.49)	(-2.40)
Firm and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	9,154	9,023	9,154	9,154	9,023	9,154
Adjusted R^2	0.67	0.64	0.68	0.67	0.64	0.68

Panel B: Measuring Credit Risk Using Bond Yield Spreads

	UIVOL as Operating Risk Measure			UCVOL as Operating Risk Measure		
	(1)	(2)	(3)	(4)	(5)	(6)
INTERCEPT	2.38***	2.32***	2.29***	2.27***	2.22***	2.21***
	(6.48)	(6.93)	(6.81)	(6.45)	(6.26)	(6.56)
TBG	-0.49	-0.82	-0.63	-0.53	-0.44	-0.45
	(-0.75)	(-0.81)	(-0.76)	(-1.09)	(-0.57)	(-0.72)
TBG*SMALL	-0.17**			-0.22**		
	(-2.09)			(-2.13)		
TBG*NONSTK		-0.24			-0.15	
		(-0.22)			(-0.92)	
TBG*NONAFF			-0.25*			-0.18*
			(-1.71)			(-1.89)
LOGSIZE	-0.04	-0.04	-0.03	-0.03	-0.02	-0.02
	(-0.99)	(-0.95)	(-0.82)	(-0.56)	(-0.53)	(-0.56)
LOGAGE	0.15*	0.14*	0.13*	0.13*	0.14*	0.13*
	(1.72)	(1.82)	(1.76)	(1.74)	(1.80)	(1.79)
PROFIT	0.02	0.01	0.01	0.01	0.01	0.01
	(0.61)	(0.32)	(0.29)	(0.37)	(0.35)	(0.32)
NONSTK	-0.24	-0.24	-0.23*	-0.23*	-0.23*	-0.23*
	(-1.47)	(-1.47)	(-1.79)	(-1.79)	(-1.75)	(-1.78)
NONAFF	0.05	0.06	0.05	0.03	0.04	0.05
	(0.82)	(1.08)	(1.09)	(0.90)	(1.16)	(1.10)
DURATION	0.05**	0.05**	0.05**	0.05**	0.05**	0.05**
	(2.55)	(2.57)	(2.40)	(2.34)	(2.32)	(2.34)
BETA	0.01	0.01	0.01	0.01	0.01	0.01
	(0.12)	(0.15)	(0.24)	(0.24)	(0.24)	(0.23)
GOVINV	0.01	0	0	-0.01	-0.01	-0.01
	(0.07)	(0.04)	(0.02)	(-0.05)	(-0.07)	(-0.07)
STKINV	0.85**	0.83**	0.83**	0.84**	0.83**	0.83**
	(2.38)	(2.45)	(2.45)	(2.37)	(2.47)	(2.45)
Firm and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	9,154	9,023	9,154	9,154	9,023	9,154
Adjusted R^2	0.55	0.53	0.55	0.55	0.53	0.55

Table 6: Regressions of Bond Portfolio Credit Risk on Alternative Operating Risk Proxies

This table reports the coefficients from panel regressions of bond portfolio credit risk measures on alternative operating risk measures, including LEVERAGE, LONG, HERFL, and HERFS. LEVERAGE is an insurer's liability to its total assets. LONG is the percentage of long tail insurance business. HERF and HERL are the measures of diversification across insurance lines and across states. All other variables are defined in the same way as in Table 4. The t-statistics adjusted for the firm and year two-way clustering are reported in the parentheses. The sample period is from 1996 to 2010. Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

	Bond Rating as Dependent Variable					Credit Spread as Dependent Variable				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
INTERCEPT	21.60***	21.61***	21.54***	21.62***	21.93***	2.26***	2.23***	2.20***	2.30***	2.21***
	(37.86)	(35.60)	(37.38)	(37.72)	(32.96)	(5.77)	(5.37)	(5.27)	(5.79)	(5.30)
LEVERAGE	0.45***				0.36**	-0.25**				-0.22*
	(2.65)				(2.41)	(-2.11)				(-1.93)
LONG		0.35*			0.17*		-0.16*			-0.14*
		(1.89)			(1.79)		(-1.82)			(-1.77)
HERFL			0.33**		0.20*			-0.22**		-0.14
			(2.17)		(1.92)			(-2.21)		(-1.50)
HERFS				0.03	0.05				0.01	0.02
				(0.15)	(0.36)				(0.16)	(0.40)
LOGSIZE	0.05	0.06	0.06	0.06	0.05	-0.01	-0.02	-0.02	-0.01	-0.02
	(1.03)	(0.91)	(1.01)	(0.94)	(0.82)	(-0.04)	(-0.79)	(-0.74)	(-0.59)	(-0.96)
LOGAGE	0.13	0.12	0.13	0.12	0.12	-0.13*	-0.12*	-0.12	-0.13	-0.12*
	(0.97)	(0.91)	(0.95)	(0.92)	(0.75)	(-1.77)	(-1.83)	(-1.61)	(-1.43)	(-1.78)
PROFIT	-0.03	-0.04	-0.03	-0.04	-0.06	0.01	0.02	0.02	0.02	0.02
	(-0.69)	(-1.01)	(-0.62)	(-1.02)	(-1.34)	(0.20)	(0.68)	(0.54)	(0.58)	(0.57)
NONSTK	0.16	0.19	0.32	0.18	0.2	-0.22*	-0.20**	-0.24**	-0.24**	-0.22**
	(1.05)	(1.19)	(1.30)	(1.13)	(1.09)	(-1.75)	(-2.06)	(-2.23)	(-2.34)	(-2.28)
NONAFF	-0.14*	-0.13	-0.13*	-0.13	-0.12	0.04	0.04	0.04	0.03	0.04
	(-1.77)	(-1.62)	(-1.66)	(-1.62)	(-1.33)	(1.22)	(1.08)	(0.94)	(0.79)	(1.06)
DURATION	-0.04**	-0.04**	-0.04**	-0.04**	-0.04**	0.05**	0.06**	0.05**	0.06**	0.05**
	(-2.03)	(-1.99)	(-2.00)	(-2.00)	(-2.07)	(2.13)	(2.19)	(2.18)	(2.23)	(2.18)
BETA	0.02	0.02	0.02	0.02	0.03	-0.01	-0.02	-0.01	-0.01	-0.02
	(0.54)	(0.49)	(0.48)	(0.50)	(0.32)	(-0.09)	(-0.13)	(-0.21)	(-0.07)	(-0.31)
GOVINV	0.27*	0.26	0.26	0.27	0.27	-0.01	-0.01	-0.01	-0.01	-0.01
	(1.66)	(1.64)	(1.59)	(1.64)	(1.59)	(-0.15)	(-0.11)	(-0.16)	(-0.13)	(-0.09)
STKINV	-0.55*	-0.65**	-0.75**	-0.65**	-0.63**	0.81**	0.65**	0.66**	0.85**	0.80**
	(-1.84)	(-2.13)	(-2.33)	(-2.12)	(-2.05)	(2.33)	(2.25)	(2.26)	(2.29)	(2.27)
Firm and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9,154	9,154	9,154	9,154	9,154	9,154	10,379	10,379	10,720	10,378
Adjusted R^2	0.64	0.64	0.64	0.64	0.66	0.55	0.54	0.53	0.53	0.55

Table 7: Panel Regressions of Insurers' Investment Performance on Operating Risk Measures

This table reports the coefficients of panel regressions of investment performance on operating risk measures and various control variables. The dependent variable is insurers' investment performance measured as the ratio of the aggregate investment income and capital gains relative to invested assets. BG stands for operating risk, measured as UIVOL or UCVOL, where UIVOL is the standard deviation of the ratios of net underwriting gain (loss) to invested assets in the prior 10 years and UCVOL is the standard deviation of the ratios of cash flow from underwriting to invested assets in the prior 10 years. Persistent operating risk (PBG) is measured as $\beta_{i,t}^{UI}$*UIVOL or $\beta_{i,t}^{UI}$*UCVOL, where $\beta_{i,t}^{UI}$ is estimated from the AR(1) regressions using data from year t-9 through t for firm i: $UI_{i,t-k} = \alpha_i + \beta_{i,t}^{UI} UI_{i,t-k-1} + \varepsilon_{i,t-k}$ $(k = 0\ through\ 9)$. TBG is the standard deviation of the residual of the regression. NONCRISIS is a dummy variable that equals to zero for 2007 and 2008 and one for other sample years. LOGSIZE is the logarithm of the book value of firms assets at the year end. LOGAGE is the logarithm of firm age, which is computed as the difference between the year of reporting and the firm incorporation year. GOVINV is the ratio of investment in government bonds to total invested assets. STKINV is the ratio of investment in stocks to total invested assets. The t-statistics (adjusting for the firm and year two-way clustering) are reported in the parentheses. The sample period is from 1996 to 2010.

	Static Background Risk Effect		Dynamic Background Risk Effect	
	(1) UIVOL	(2) UCVOL	(3) UIVOL	(4) UCVOL
Intercept	2.85***	2.94***	3.00***	3.01***
	(7.49)	(7.62)	(7.15)	(7.16)
NONCRISIS	0.84***	1.05***	0.79***	0.80***
	(10.98)	(14.62)	(18.78)	(21.47)
BG	2.98***	1.90***		
	(3.29)	(3.60)		
BG*NONCRISIS	-2.70***	-1.59***		
	(-3.39)	(-3.54)		
PBG			2.58***	1.51***
			(4.12)	(2.68)
PBG*NONCRISIS			-2.12***	-1.38***
			(-3.09)	(-2.50)
TBG			0.34***	0.23**
			(0.72)	(0.71)
TBG*NONCRISIS			-1.05***	-0.64***
			(-3.94)	(-3.12)
LOGSIZE	0.14***	0.15***	0.11***	0.12***
	(3.33)	(3.26)	(3.43)	(3.48)
LOGAGE	-0.92***	-0.97***	-1.06***	-1.06***
	(-8.06)	(-8.43)	(-8.37)	(-8.40)
NONAFF	-0.27**	-0.27***	-0.27**	-0.27**
	(-2.54)	(-2.61)	(-2.39)	(-2.37)
NONSTK	0.62	0.66	0.66	0.65
	(1.49)	(1.44)	(1.52)	(1.51)
Firm Dummies	Yes	Yes	Yes	Yes
N	13,244	13,244	12,383	12,383
Adjusted R^2	0.211	0.202	0.232	0.233

Figure 1: Difference in Credit Risk Taking between Top and Bottom Decile Insurers

This figure shows the spreads between D10 and D1 portfolios sorted by operating risk measures over time. The first two panels are for the differences between rating spreads across D10 and D1 decile portfolios sorted by respective operating risk measures. The later two panels are for the differences of credit spreads across D10 and D1 decile portfolios sorted by respective operating risk measures. UIVOL is the standard deviation of the ratios of net underwriting gain (loss) to invested assets in the prior 10 years. UCVOL is the standard deviation of the ratios of cash flow from underwriting to invested assets in the prior 10 years.